How Entrepreneurship, Culture and Universities influence the Geographical Distribution of UK Talent and City Growth

"Cities' roles as centres of knowledge flows and creativity are the key determinants of their competitiveness"

Tsang, D (2005:p. 1331)

1. Introduction

The creation and distribution of human capital, often termed talent, has been recognised in economic geography as an important factor in the locational decisions of firms (Florida, 2002), and particularly in the context of innovation emanating from universities (Sternberg, 2014; Audretsch and Caiazza, 2016; Caiazza, 2016). At a more general level, talented workers and entrepreneurs are seen as a key driver of economic growth (Romer, 1990). An interesting debate has also been considering the question of what spatial level we should consider when examining these theories of talent distribution, knowledge industries and economic growth. The early work of Jacobs (1961) argued that cities play an important role in attracting and integrating talented people, whilst Ullman (1958) considered similar issues in the context of regional economic development, and Lucas (1988) makes a broader argument that clustering of talented people drives productivity growth which in turn raises incomes at the city and regional level. Berry and Glaeser (2005) contend that it is entrepreneurs choosing knowledge intensive modes of business that drive clustering of skilled people in cities, whilst Faggian and McCann (2006), and Florida (1999) argue that universities act as a conduit to bring talent into cities. Interestingly, Greene et al (2006) argue that the shift in focus away from cities (to city regions and regions) in the UK as the analytical point of focus has been largely driven by political expediency rather than theoretical or empirical considerations. It is certainly true, however, that much of the early US contribution to this empirical literature focuses on regions and regional economic systems (Glaeser, 2000; Simon, 1998), although more generalisable findings are that human capital is fundamental to economic growth (Lange and Topel, 2004) and that growth and innovation are highly correlated with openness and creativity. These findings led Thurik et al (2013) to argue that dynamic entrepreneurial capitalism needed a more pervasive and wider focused policy approach from governments than simply promoting entrepreneurship per se, and that policy should be supportive of creating an entrepreneurial economy in which culture, talent and knowledge are allowed to flourish (Markuerkiagan et al, 2016).

But there now exists a significant body of work at the city level too (Glaeser et al, 2001; Lloyd, 2001, Florida, 2002; Moretti, 2013; Storper, 2013) examining similar issues, and often generating similar results. What tends to differentiate the city level work from the regional level work is the inclusion of new types of variables in analysis covering interesting issues and characteristics (such as culture, public amenities, arts, and other more lifestyle orientated and social considerations) that differentiate one city from another even within a region, although Efrat (2014) did examine the effects of Hofstede's cultural dimensions on national level innovation and found them to be important both directly and indirectly. This broader focus is a significant departure from the more traditional thinking that assumed that people act (more or less solely) on the basis of economic factors such as jobs and potential future income streams in making their locational decisions.

This paper takes this latter body of work, in particular the work of Florida (2002), as its theoretical and empirical point of departure to investigate the economic geography of talent in the one hundred largest cities (measured by population) in the UK. As far as empirically possible, it replicates the Florida *op cit* US paper by focusing on identifying city level factors in the UK that attract talent (human capital). The general starting hypothesis is that talent is attracted by human and economic diversity and that subsequent geographic concentrations of talent impact on innovation and wealth (or incomes) at the city level.

The rest of the paper is organised as follows. In Section 2 the relevant theoretical and empirical literature is reviewed to provide insight and context. Section 3 outlines the nature of the data used in the empirical analysis and the econometric methods employed. In Section 4 the key data is described to highlight general relationships between key variables and the city distributions, along with the econometric estimates of talent distribution across the one hundred largest cities of the UK. Conclusions and implications are drawn in Section 5.

2. Literature Review

Over the last few decades, the socio-economic experiences of cities and regions have varied substantially. Whilst some of this dispersion can be explained by purely geographic factors, the really interesting questions relate to economic growth and quality of life and how these impact on peoples' locational decisions. Yet these questions have not been fully answered, despite a widening body of research of mainly US origin[1].

Glaeser et al. (1995), for example, in their examination of the growth experiences of 203 large US cities, explicitly focus on human capital as a determinant of city growth. Further, they strongly argue that there is a need to focus research attention on cities as they operate as open economies with 'tremendous movement of capital, labour, and ideas' (p.118). And cities are more specialised and less arbitrary units of socio-economic activity than regions (or countries). This focus on knowledge (Caiazza et al, 2015) and the transfer of ideas (Caiazza and Volpe, 2016) accords with established theory such as Romer (1986) on disembodied knowledge, Lucas (1988) on human capital and Porter (1990) on high-tech clustering.

So what does previous research tell us about city and regional growth? Glaeser et al (1992) found evidence that cross-industry intellectual externalities were particularly important for urban growth. The later, Glaeser et al. (1995), work found that population migration responds to growth opportunities and importantly, that movements in wages and population are primarily determined by productivity not quality of life changes. Yet this is disputed by Shapiro (2006), also using US evidence, who finds that only 60% of employment change at the city level can be explained by productivity. This leaves the remaining 40% to be explained by quality of life measures and other, non-economic factors. Another important contribution by Gabriel and Rosenthal (2004) found substantial differences between what businesses regard as high quality cities and what people regard as high quality (of life) cities. Further, they also found that employment growth depended upon quality of business environment not quality of life. This is further confused by the UK empirical evidence from Fingleton (2003) who found that the key determinant of efficiency variations across areas relates to differences in workers ability to make use of available technology. As Storper and Scott (2009) argue, the key question of the causal relationship between human capital and urban growth has not been answered.

Thus, on the basis of the empirical evidence presented, we might conclude that human capital is important as a determinant of city (and regional) growth, but the

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[1] UK research has been constrained until quite recently by lack of quality data below the regional level

mechanisms by which this occurs are less clear. We are unsure about what role, if any, quality of life plays, and how we can link in human capital, innovative capacity, innovation and subsequent economic growth. If we took the most common approach adopted by economists we would end up with a model which allows for cities to differ only in their productivity and quality of life. Thus a city output model could take the form:

$$A_{i,t}\, f\,(L_{i,t}) = A_{i,t} L^{\sigma}_{i,t} \qquad (1)$$

where, $A_{i,t,}$ productivity in city i at time t, $L_{i,t}$ is the population, and f (.) is a Cobb-Douglas production function with a common parameter σ. From this the wage of the potential migrant would equal the marginal product of labour, and total utility could be defined as wages multiplied by a quality of life index of the form:

$$\text{Quality of Life} = Q_{i,t}\ L^{-\delta}_{i,t} \qquad (2)$$

where $\delta > 0$, and quality of life captures a wide range of factors e.g crime, environment, housing etc.

From this total utility of a potential migrant to city i is :

$$\text{Utility} = \sigma\ A_{i,t} Q_{i,t}\ L_{i,t}^{\sigma-\delta-1} \qquad (3)$$

This type of framework would be suitable for estimating city growth models, but raises a few issues about heterogeneity of labour which of course is a fundamental aspect of human capital theory in this context. It is also the case that this kind of structure does not really enlighten us about how human capital feeds through the socio-economic system, and in particular how it impacts on innovative capacity.

In this context, one particularly interesting sub-group of the population, in both an economic and quality of life context, is (primarily young) people who enter a process by which they attend a Higher Education Institution, subsequently graduate, and either enter the labour market or drop out of it. Pietro (2006) in his analysis of university drop-out rates in Italy, shows that the state of the local labour market significantly affects the stay or drop-out decision which has implications for the quality of human capital available. The locational decisions of these individuals, and flows that derive from these decisions are hugely interesting, and of great importance, as they possibly represent the greatest flow of human capital around a region or country at a given point in time. And further, they have fewer geographical mobility barriers thus are more closely aligned to the open economy model of the city or region. It is also the case that an individuals' decision over choosing an HEI might be quite different than their labour market decision post-graduation (Cowling and Pollard, 2008). Specifically, we might *a priori* expect that quality of life issues might be more important in the HEI decision than the labour market decision. Yet there may be an element of hysteresis with graduates becoming reluctant to move from their HEI location if they enjoy the quality of life. In this respect, what we seek to estimate is an augmented city level production function which clearly differentiates between different types and levels of human capital or talent. This is consistent with a significant body of production function, inequality, skills biased technical change, and economic growth work which commonly finds that the returns to different levels of human capital are very different (Barro, 2001; Hanushek, 2013; Murphy and Topel, 2014)

The multivariate models can estimate the dynamic inter-relationships between human capital (talent), innovative capacity, and economic value added. These can be estimated, using talent as an example, in the form:

$$\text{Human Capital Measure}_i = \alpha_{0i} + \alpha_{1i}\,\text{Innovative Capacity} + \alpha_{2i}\,\text{Quality of Life} + \alpha_{3i}\,\text{Labour Market Indicators} + \alpha_{4i}\,\text{Economic Indicators} + \alpha_{5i}\,\text{HEI Indicators} + \beta_{6i}\,\text{Population Demographics} + \beta_{7i}\,\text{Population} + \upsilon_i$$

Thus for our new graduate talent human capital measures we could hypothesise that the ability of a locality to retain its incoming as students and graduates is related to the innovative capacity of that locality, as well as quality of life, labour market conditions, general economic conditions. The second part of the system which captures local innovative capacity should in itself be a function of the stock of human capital as well as other population size and demographic variables.

To conclude, we hope to shed more light on the factors that determine the locational decisions of talent, and the extent to which this is associated with into local innovation systems and innovative capacity and economic value added. The potential new insights of this research are that it explores the impact of quality of life and economics on the locational decisions of talented people in the UK. That it focuses on the city as a unit of analysis, and that we expand the range of talent measures to consider new graduates.

3. Data and Methods

The core variables for analysis can be classified into eight categories, namely; (1) diversity, (2) technology & innovation, (3) talent, (4) entrepreneurship, (5) housing, (6) culture, (7) population, and (8) value add. Table 1 describes the measures adopted in relation to each of the eight categories. In the following we set out a theoretical justification for each of these categories. The data refer to the 100 largest cities, by population, in the UK excluding the capital city London. London is excluded as it is 50 times larger than the average UK city and is a truly international city.

Talent

The basic talent measure is simply the proportion of the adult population with an undergraduate degree and above. This data is derived from the 2001 population census. Four additional measures of talent are also used which relate to recently graduated university students. These four measures are derived from the Higher Education Statistical Agency (HESA) Destinations of Leavers Survey which tracks graduates as they begin their working lives post-university. The student and graduate information comes from UCAS applications database and HESA destinations of leavers from higher education survey. The UCAS data has the potential to allow postcode tracking of applicants to HEIs in the UK. The HESA data gives us postcode information on domicile, HEI and employer location as well as other alternative labour market states between 4 and 9 months after graduation. The 2004/05 HESA data has information on 258,420 full-time graduates and a further 60,840 part-time graduates giving a total of 319,260 complete records. The 2003/04 data gave a total of 313,040 records. This would then be integrated with other local labour market, economic, innovation and quality of life data at two spatial levels. The largest unit would be the 36 NUTS 2 areas of Great Britain, and the smallest the Local Authority (city) level. It is this latter spatial dimension that this research considers.

The measures are all defined as the proportion of graduates out of the total relevant population. The first, new female talent, relates to female graduates who left their home to move to a new university city and then subsequently remained in that city after graduation. As such it represents a talent flow into the host university city. The second, new male talent, is the equivalent for male graduates. The third measure, new talent in talented jobs, represents new graduate talent into a host university city who were working in graduate level employment within six months of graduation. The fourth measure, new talent in talented jobs, relates to the proportion of new graduate talent with 1st Class or Upper 2nd Class degrees who moved to their university city and remained in that host city after graduating.

Culture

Cultural activities are, controversially, seen as a crucial factor in attracting and retaining talent (Florida and Mellander, 2015). Several measures of cultural amenities are combined into a culture domain constructed by the UK government as a component of its Index of Multiple Deprivation. The items included in this domain are sports & leisure facilities, theatre & concert halls, and parks & open spaces.

Entrepreneurship

Similarly, the relationship between entrepreneurship, talent and economic performance is an important one (Bosma and Sternberg, 2014). One measure of openness and vibrancy is the inflow of new, entrepreneurial, businesses as entrepreneurs start up new firms to take advantage of perceived new market opportunities and gaps in the provision of goods and services. In this respect the measure is the proportion of new firms normalised as a percentage of the existing stock of firms. This variable is captured for two time periods, 1997 and 2003, and is derived from UK government VAT statistics.

Diversity

Diversity is now widely, if controversially, seen as important in attracting talented workers who might be attracted to tolerant areas (Florida, 2005; Lee, 2016). The measure of diversity refers to the ethnic diversity of the population. It is derived from the 2001 population census and reflects the proportion of the total population who do not classify themselves as White British. In this sense it is a locational quotient.

Housing

Here the measure is representative of the average Council Tax bill for individuals. This is a local tax falling on the individual household. This is an alternative to house prices which are subject to substantial inter-temporal variability. It can be argued that Council Tax captures quality and size of housing, as well as local provision of public goods and services which makes it more suited to this research. This is derived from government statistics for the UK.

Gross Value Added

This measure is gross value added per worker and is derived from the population census for 2001 and government input-output tables. As such, it is total gross value added created by the working population of each city divided by the working population. Alternative measures such as income per capita were also available.

Technology

As technology and innovation is associated with productivity growth and hence growth in real incomes, the measure here is the proportion of the total business stock that can be classified as operating in knowledge based industries. This is available for 1997 and 2003. It is derived from government statistics and calculated using detailed industry codes.

Population

As a control variable, but also as an interesting variable in its own right, the size of the population is also included. This is derived from the population census for 2001. City size is important as the largest cities are often an attractor of company head offices and generally have important historical and cultural legacies that may impact on an individuals' locational decision.

University

It is also the case that some UK cities have universities that were founded hundreds of years ago and are woven into the culture of a city as well as being a major actor in the socio-economic system of a city. And research has highlighted considerable difference in labour markets between university and non-university cities in the UK (Cowling, 2008). This data is derived from the Higher Education Funding Council (HEFCE).

4. Findings

Here the basic data for key variables is described prior to an examination of key relationships by multivariate analysis. This is intended to provide an overview of the economic geography of talent, prior to the multivariate analysis.

The Economic Geography of Talent

The economic geography of talent is very uneven across UK cities. On average 28 per cent of the population of the largest 100 UK cities had a university degree of above in 2001. Yet cities like Oxford and Cambridge, not surprisingly, have high graduate shares amongst the local population, accounting for 53.3 per cent and 46.8 per cent of the population. Both are higher than the top-ranked region of Washington DC at 42 per cent reported in Florida (2002). Other UK cities with high graduate shares are Brighton, Bradford, Winchester, and Harrogate, all cities with over 40 per cent graduate shares. However, this contrasts with Ipswich, which has the lowest graduate shares at 14.9 per cent, and Blackpool, Stoke-on-Trent, Dover and Colchester, cities that all have graduate shares considerably below 20 per cent. The interesting feature is that these cities are geographically diverse being located widely across UK regions.

Using a broad measure capturing average new graduate talent to university cities across our four new graduate talent variables, the findings are equally uneven. The highest ranked UK city for retaining new graduate talent from outside is Belfast at 61.2 per cent. Glasgow, at 42.3 per cent, Aberdeen, at 40.3 per cent, and Edinburgh, at 36.7 per cent, also rank highly. The notable feature is that these are all historically important, large cities, in Northern Ireland and Scotland. Cities with the lowest new graduate talent retention are Colchester, at 5.4 per cent, Wallsall, at 6.7 per cent, Lancaster, at 7.9 per cent, Chelmsford, at 8.3 per cent, and Canterbury, at 8.4 per cent.

Table 2 (see Appendix) presents correlation analysis results. From Table 2 it can be observed that technology is correlated with talent, entrepreneurship and incomes all in a positive, and significant, way. And these relationships appear fairly stable over time. Talent, *per se*, is correlated with the presence of a university in a city, higher entrepreneurial activity, higher culture index scores, and higher incomes. Entrepreneurship, *per se*, is correlated with higher culture index scores and higher incomes. It is also noted that larger sized cities are also correlated with more graduate talent of all types, and also with more talent in general. Further, new graduate talent is correlated with better housing and public goods and services. So these correlations provide some support for the *a priori* hypotheses drawn from Florida (2002) positing linkages between talent, technology and incomes. An interesting aspect is the additional link, or mechanism by which this might occur, which allows a role for the entrepreneur. And the possible inherent advantages that large cities have in attracting inflows of new talent to add to their existing higher stocks of talent is also noteworthy.

Culture

The results of the correlation analysis indicate that talented people appear to be attracted by cultural amenities. The correlation coefficient for the basic talent index and culture index is positive and significant (0.281, Table 2). Figure 1 graphically depicts this relationship and places the 100 cities in talent and cultural space. This is consistent with recent research by Cowling and Pollard (2008) using the 2007 graduating cohort at the University of Sussex survey as a case study for analysis. Their research identified good public transport, availability of affordable housing, good restaurants etc., and good standard of public healthcare as key factors in graduating students' locational decisions.

New Graduate Talent

The results of the correlation analysis indicate that talented people and the ability to retain new graduates from outside are correlated. The fact that the talent measure predates the new graduate talent measure might suggest that newly graduating talented people are attracted by higher levels of (existing) talentent. The correlation coefficient for the basic talent index and new graduate talent index is positive and significant (0.395, Table 2). Figure 2 graphically depicts this relationship and places the 100 cities in talent and entrepreneurship space.

Entrepreneurship

The results of the correlation analysis indicate that talented people and entrepreneurship are correlated. The fact that the entrepreneurship measure predates the talent measure might suggest that talented people are attracted by higher levels of entrepreneurial activity. The correlation coefficient for the basic talent index and entrepreneurship index is positive and significant (0.473, Table 2). Figure 3 graphically depicts this relationship and places the 100 cities in talent and entrepreneurship space.

Diversity

The results of the correlation analysis indicate that talented people and diversity are not associated with one another. The correlation coefficient for the basic talent index and diversity index is positive but not significant (0.009, Table 2). Figure 4 graphically depicts this relationship and places the 100 cities in talent and diversity space.

Housing

The results of the correlation analysis indicate that talented people and housing are not associated with one another. The correlation coefficient for the basic talent index and housing measure is positive but not significant (0.051, Table 2). This might bring into question the contention that talented people are willing to pay more for better public provision of goods and services at the local level. However, for new graduate talent the correlation is positive and significant (0.319, Table 2). This might suggest that housing and public provision of goods and services have become more important for attracting talent.

[Insert Figure.1: Culture and Talent across UK cities here]

[Insert Figure 2: Average New Graduate Talent and Talent across UK Cities here]

[Insert Figure.3: Entrepreneurship and Talent across UK Cities here]

[Insert Figure.4: Talent and Diversity across UK Cities here]

5. Multivariate Findings

Multivariate analysis was used to explore these issues in more detail in an attempt to isolate more robust relationships between talent and its economic geography. As there are three core dependent variables of interest, namely; talent, technology and income, two of which are expressed as percentages, and bounded between 0 and 1, the most appropriate modelling strategies differ. In the case of talent and technology, both of which are bounded, the most suitable method is the fractional logit. Given the bounded nature of the two dependent variables of interest, the share of the population with a graduate degree, and the share of the business stock accounted for by knowledge based industry, the most appropriate form of estimation model is a fractional logit. The modelling of these sorts of allocation to various categories have generally taken the form of structural equations models, doubly censored tobit models, or more simplistic regression-based models. However, there are limitations associated with these approaches. While the structural equations and regression approaches cannot guarantee allocation predictions that are plausible and sum to the total available, the doubly censored tobit models are computationally more burdensome when attempting to model skills allocation among competing activity categories (here degree level talent and other educational qualifications).

A methodology that can overcome these limitations is the fractional logit model. The fractional logit model offers a powerful framework for predicting allocations among various activity types (Ye and Pendyala, 2004) because each allocation constitutes a "fraction" of the total available (here educational qualifications). Thus the fractional logit model ensures consistency in prediction and provides behavioural sensitivity through the incorporation of explanatory variables that influence allocation patterns (here city demographics, personal demographics, industry mix and culture effects). As gross value added per capita is expressed in absolute, cash, terms this easily lends itself to Ordinary Least Squares analysis, although even in this case robust regression models are estimated.

Talent

Table 3 shows the core talent models. It can be observed that entrepreneurship is significantly associated with talent across models with a coefficient around 0.18 (at the 0.0001 level of significance). This suggests that entrepreneurial activity can act as an attractor of talent at the city level. It was also found to be the case that culture was significantly associated with talent across model specifications with a coefficient around 0.09 (at the 0.03 level of significance). This differs from the null result reported by Florida (2002) for the effect of culture on talent in US cities. In addition, the presence of a university in a city was found to have the strongest association with talent with a coefficient around 0.20 (at the 0.01 level of significance). In these models, no significant relationships were identified between population size, housing, or diversity, and talent. This result supports some of the existing literature. Champion and Townsend (2011) have highlighted the relatively poor performance of larger UK cities at this point in time, while Lee (2011) finds that while diversity is important for growth in British cities, human capital matters more.

New Graduate Talent

Table 4 shows the new graduate talent models using the four alternative measures. Model 1 shows that new female graduate talent is associated very strongly with existing talent. This is also supported for new male graduate talent in Model 2 with a similar size of coefficient (2.62 for females compared to 2.68 for males) and level of significance (0.003 compared to 0.007), and in Model 3 for new graduate talent with a graduate job (coefficient 2.46, significance 0.005), and in Model 4 for new super talent (coefficient 2.21, significance 0.008). These findings suggest that there is a positive, and mutually reinforcing, dynamic at the city level with high, historical, stocks of graduate talent in the population acting as an attractor to new, incoming, graduates, who then add to the existing stocks etc etc. It also implies that cities who begin with low graduate stocks will find it very difficult to change their relative position and add to their smaller stocks of talent.

The results also show that entrepreneurial activity is also associated with attracting new male graduate talent and new super graduate talent (coefficients of 0.33 and 0.37 respectively, significance 0.04 and 0.03 respectively). This was not the case for new female graduate talent or for new graduate talent in graduate jobs. In contrast, the housing variable was found to act in a positive, and significant, way on new graduate talent across all four models with coefficient ranging from 1.59 for new super graduate talent to 1.77 for new male graduate talent. Across all four models significance levels were below 1 per cent. The new graduate talent models all show a significant association with population size of city. In short, new graduate inflows of talent to a university city are attracted to larger cities. This is particularly so for graduates working in graduate level jobs (coefficient=0.48, significance 0.01), and for male graduates more than female graduates (coefficients of 0.41 compared to 0.35 respectively). In three of the four new graduate talent models culture is positively associated with new graduate talent. The association was highest for graduate super talent (0.14, significance 0.02), and also higher for males than females (coefficient 0.17 compared to 0.12 respectively).

These new graduate talent findings, compared to the general stock of talent findings, are more consistent with the underpinnings of the model outlined by Florida (2002) in that new inflows of graduate talent are attracted by a wider variety of economic and social (quality of life) considerations. Whilst there is commonality and consistency in the findings in respect of the positive influences of entrepreneurial activity and culture on talent, the attraction of new inflows of graduate talent are also associated with quality of housing and public provision of goods and services and a preference for larger cities. These differences are important as they will affect the relative position of cities in respect of talent accumulation in the future. As noted previously, new graduate talent also appears to gravitate towards cities that already have relatively high talent stocks, which makes it even more difficult for cities playing catch-up.

Talent and Knowledge-Based Industry

The focus of the analysis now develops to explore relationships between talent and knowledge-based industry activity. From Table 2 it is evident that talent is highly correlated with knowledge industry (coefficient 0.420). Knowledge industry is also correlated with entrepreneurship (coefficient 0.797), and culture (coefficient 0.271), but not with housing or diversity. Figure 5 graphically depicts the relationships between diversity and knowledge-based industry, and shows a slight, but statistically insignificant, positive relationship. Figure 6 shows the strong and positive relationship between talent and knowledge-based industry.

[Insert **F**igure.5: Technology and Diversity across UK Cities here]

[Insert **F**igure.6: Technology and Talent across UK Cities here]

Multivariate (fractional logit glm) models were used to further explore these potential relationships. From Table 5, it is observed that knowledge-based industry is associated with talent in a positive and significant way (coefficient 0.87, significance 0.006), diversity (coefficient 0.29, significance 0.045), and entrepreneurship (coefficient 0.23, significance 0.0001). No associations were found between knowledge-based industry and housing, culture or city size. The results are consistent with those reported by Florida (2002), although he uses a tech-pole index measure based on concentrations of high-technology output.

What these findings suggest are that the availability of talent is an important factor in the locational decisions of knowledge-based industry. But this not only applies to potential talented workers, but more widely to entrepreneurs. This latter aspect is intriguing and might be explained by the desire to create clusters of knowledge-based activity and the types of social and business networks which, if successful, can promote mutually beneficial generation and exchanges of new ideas and technologies. This, in the UK, was the rationale under-pinning the creation of Science Parks. It also brings into question the relative importance of local taxes and physical amenities which many public sector regional development agencies consider to be crucial factors in attracting knowledge industries.

Talent and Gross Value Added (GVA)

In micro and macro economics researchers have hypothesised and proven a strong and significant relationship between human capital and income and human capital and productivity at all spatial levels from countries down to small localities. In addition, the role of technology in enhancing productivity and ultimately, income and wealth has also been widely investigated again at all spatial levels. Here similar relationships are explored at the city level in a multivariate framework using robust OLS models.

The models generally show that there is a relationship between knowledge-based industry activity and gross value added (coefficient 2.83, significance 0.0001) which reconfirms its fundamental importance to productivity. Talent was also positively associated with gross value added (coefficient 0.66) as was diversity (coefficient 0.32). It is also interesting to note that there was a negative relationship between city size and gross value added (coefficient -0.18) which might suggest that, on average, larger cities are implicitly less efficient holding talent and other factors constant. There is also some partial evidence that the relationship between city size and GVA is non-linear. Here the city size coefficient is positive suggesting that at some point in the city size distribution cities begin to become more productive. Or put more simply smaller and larger cities are more productive than medium-sized cities.

The predicted nadir in terms of gross value added is for cities around the 400,000 – 500,000 population level. Given that the average population size of city was 211,000, and the median city size 177,000, this might suggest that further population growth might be associated with a decline in GVA per capita, unless this was a huge population explosion taking a city up to 600,000 people. This is extremely large by UK standards. In fact at the 90th percentile in the city size distribution the average city size is only 315,000 people.

5. Conclusions

This paper set out to consider the economic geography of talent in the 100 largest cities in the UK in an attempt to understand more about what shapes and drives this spread of talent and the economic consequences of having more (or less) talent. Drawing on a framework adopted by Florida (2002) for 50 MSA areas in the

US, the *a priori* predictions were that talent is attracted by culture, diversity, and a new measure, the presence of an entrepreneurial culture as well as other more conventional factors such as the presence of technology and knowledge based industry. This paper, further adds to our understanding of the economic geography of talent by incorporating four new measures which relate to new university graduates. But important, we then augment this analysis by considering what effects on cities economies talent has in shaping the presence of knowledge based industries, and on city level productivity.

The general findings are that talent is unevenly concentrated in certain cities of the UK. Our analysis shows that talent is not particularly attracted by diversity, but more generally by culture and cultural amenities, and the presence of an entrepreneurial culture captured by lots of people starting new businesses. However, new graduate talent is associated with a much broader set of city attributes, including a preference for larger cities *per se*, the presence of a large stock of existing graduate talent and high levels of provision of public services and good housing. Of course, this means that it is likely to be very difficult for cities with low existing levels of talent to 'catch-up' with more 'talented' cities as a disproportionate share of new talent will be attracted to those cities already best placed in this respect.

Knowledge based industry, however, is associated with diversity, entrepreneurial cultures, and talent, thus establishing a link between the attraction, and retention, of talent, creativity and innovation. Further, the evidence also points to the presence of more knowledge based industry activity and higher gross value added at the city level. Holding knowledge based industry activity constant, there is also an independent effect from having more talent available in a city. These latter findings suggest that economic based, human capital, models are important in explaining the geographic differences observed in the location of knowledge based economic activity and economic performance. But if we take a step back from this final outcome, our findings shed more light on the key drivers relevant to attracting new talent to cities. This is what Florida (2002) refers to as 'creating an environment or habitat that can attract and retain talent, or human capital' (p.754), and our findings suggest that creating an entrepreneurial culture, together with high levels of provision of public goods and services are important in this respect.

Again the findings lead to similar conclusions arrived at in the US work of Florida *op. cit.*, who argues that these types of results give local policy-makers new tools for intervention rather than relying on subsidies to attract firms and industries. More specifically, policy measures that are explicitly designed to promote and support entrepreneurial activity may play a key role. Equally, local level expenditure on, and the provision of high quality public services and cultural amenities can play a key role in shaping the locational decisions of talented people. This has wider implications for local taxation decisions on the revenue and cost side.

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Table 1: Descriptive statistics

Variable	Obs	Mean	Std Dev	Min	Max
Housing (Council Tax, £s)	88	904.11	100.99	576.24	1171.54
Diversity (Fractional Ethnic)	83	0.16	0.13	0.03	0.70
Technology (Knowledge Business 1997)	93	0.17	0.05	0.10	0.38
Technology (Knowledge Business 2003)	93	0.20	0.06	0.12	0.43
Talent (Degree)	93	0.28	0.08	0.15	0.53
Talent (College)	93	0.16	0.03	0.10	0.23
University (1,0)	95	0.58	0.50	0	1
Entrepreneurship 1997	95	0.03	0.01	0.01	0.06
Entrepreneurship	95	0.03	0.01	0.01	0.06

2003					
Culture Index	82	0.00	1.00	-1.94	2.59
Income per Capita 2003 (£s)	80	10,363	2,124	7,700	19,269
Gross Value Added per worker 2002 (£s)	93	0.029	0.004	0.022	0.041
New Female Talent	50	0.19	0.11	0.02	0.58
New Male Talent	50	0.19	0.11	0.06	0.67
New Talent in Talented Jobs	50	0.17	0.11	0.05	0.63
New Super-Talent	50	0.19	0.10	0.06	0.57
Population	95	211,158	138,616	78,833	977,087

Table 2. Correlation Analysis Results

	Housing	Diversity	Technology, 1997	Technology, 2003	Talent	University	Culture	GVA per worker	New Female Talent	New Male talent	New Talent in Talented Jobs	New Super Talent	Population
Housing	1.00												
Diversity	-0.14	1.00											
Knowledge 1997	-0.11	0.13	1.00										
Knowledge 2003	-0.04	0.09	**0.93**	1.00									
Talent	0.05	0.01	**0.42**	**0.57**	1.00								
University	-0.00	0.00	-0.01	0.03	**0.31**	1.00							
Culture	-0.11	-0.09	0.20	**0.27**	**0.28**	0.08	1.00						
GVA per worker	-0.13	**0.31**	**0.68**	**0.64**	**0.27**	**0.34**	-0.01	1.00					
New Female Talent	**0.31**	-0.04	0.03	0.10	**0.36**	0.15	0.07	0.02	1.00				
New Male Talent	**0.31**	0.03	0.12	0.18	**0.42**	0.23	0.13	0.03	**0.93**	1.00			
New Talent in Talented Jobs	**0.30**	0.11	0.10	0.15	**0.37**	0.16	0.03	0.11	**0.94**	**0.96**	1.00		
New Super Talent	**0.33**	0.00	0.11	0.18	**0.39**	0.18	0.11	0.08	**0.96**	**0.96**	**0.94**	1.00	
Population	0.14	0.19	-0.12	-0.09	0.03	**0.24**	-0.08	-0.11	**0.44**	**0.40**	**0.44**	**0.37**	1.00

Table 3. Regression Model Findings for Talent

	Dependent Variable: Talent (BA and above)			
	Model 1		Model 2	
Variables	Coefficent	P>z	Coefficient	P>z
Diversity	0.139	0.408	0.147	0.398
Entrepreneurship	0.180	0.000	0.179	0.000
Housing	0.505	0.114	0.505	0.159
Culture	0.086	0.025	0.086	0.021
University	0.202	0.008	0.204	0.008
Population			-0.002	0.983
population squared			-0.000	0.864
Observations	77		77	
log likelihood	-30.41		-30.41	

Table 4. Regression Model Findings for New Talent

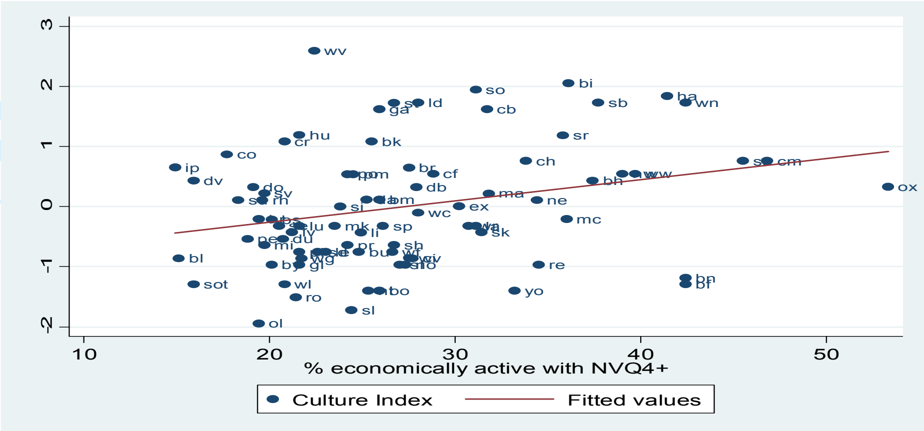
	Dependent Variables							
	New Female Talent		New Male Talent		New Talent in Talented Jobs		New Super Talent	
Variables	Coef	P>z	Coef	P>z	Coef	P>z	Coef	P>z
Existing Talent	2.618	0.003	2.681	0.007	2.459	0.005	2.205	0.008
Diversity	-0.102	0.829	0.205	0.670	0.195	0.685	0.135	0.761
Entrepreneurship	0.356	0.105	0.326	0.043	0.307	0.106	0.367	0.034
Housing	1.676	0.011	1.769	0.003	1.514	0.004	1.590	0.002
Culture	.0120	0.096	0.174	0.006	0.082	0.206	0.149	0.017
Technology	-5.340	0.187	-7.451	0.005	-5.016	0.139	-5.068	0.096
Population	0.353	0.077	0.410	0.010	0.484	0.014	0.342	0.034
population squared	0.004	0.405	0.002	0.553	0.003	0.541	0.002	0.716
Observations	41		41		41		41	
log likelihood	-12.52		-12.69		-11.53		-12.48	

Table 5. Regression Model Findings for Knowledge Based Industries

	Dependent Variable: Knowledge Based Industry			
	Model 1		Model 2	
Variables	Coefficent	P>z	Coefficient	P>z
Talent	0.866	0.006	0.903	0.006
Diversity	0.290	0.045	0.283	0.053
Entrepreneurship	0.234	0.000	0.235	0.000
Housing	0.089	0.695	0.081	0.735
Culture	0.029	0.244	0.030	0.230
University			-0.021	0.679
Population			0.018	0.778
population squared			0.000	0.900
Observations	77		77	
log likelihood	-26.03		-26.03	

Table 6. Regression Model Findings for Gross Value Added

	Dependent Variable: GVA			
	Model 1		Model 2	
Variables	Coefficent	P>z	Coefficient	P>z
Talent	0.769	0.024	0.662	0.039
Technology	2.842	0.000	2.826	0.000
Diversity	0.259	0.174	0.321	0.083
Housing			0.188	0.403
Culture	-0.017	0.510		
Population	-0.175	0.020	-0.181	0.015
population squared	0.005	0.121	0.005	0.106
Observations	77		77	
Adjusted Rsq	0.478		0.502	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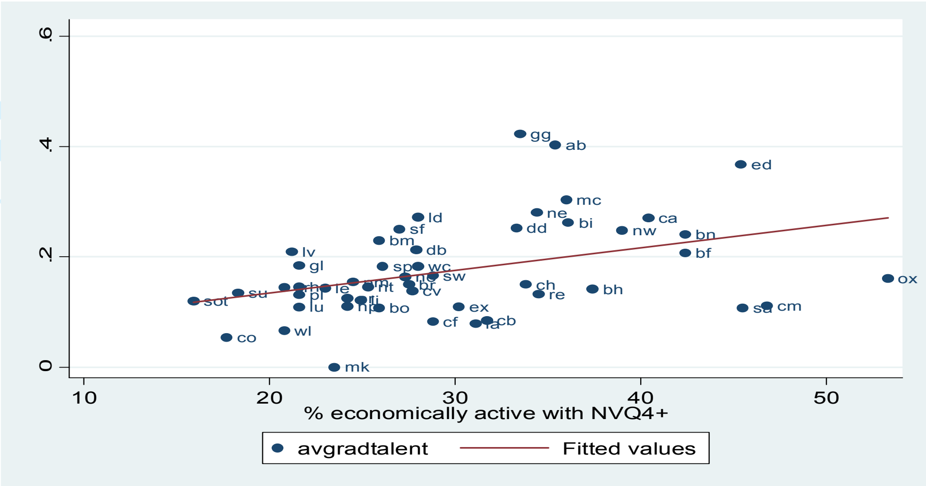

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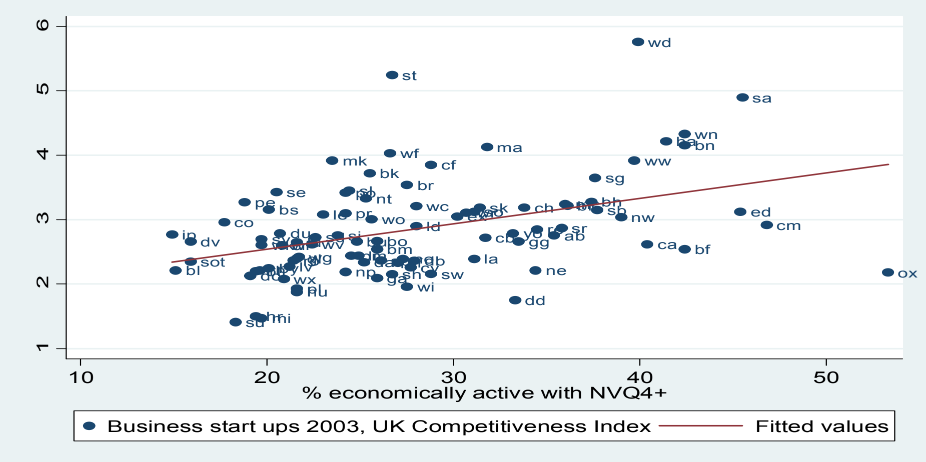
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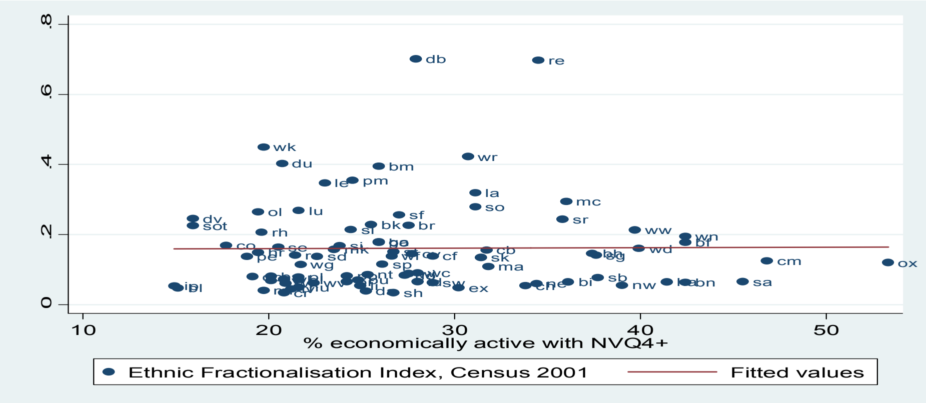
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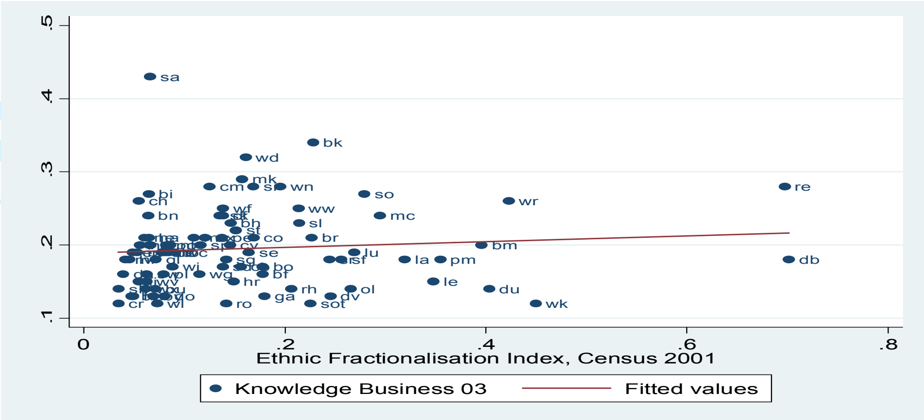
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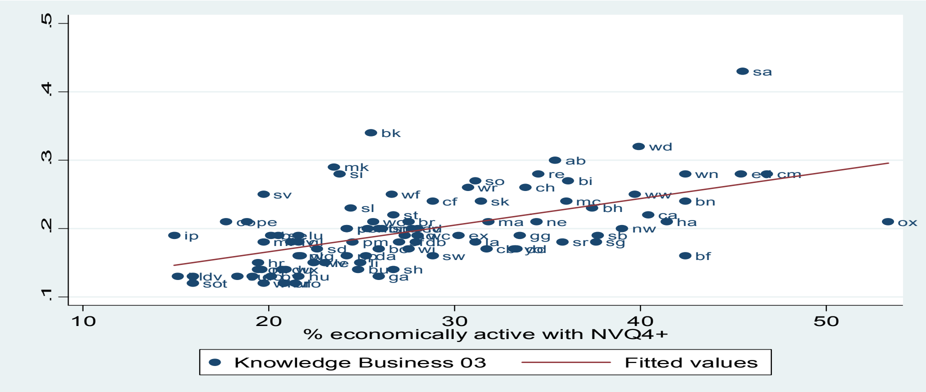
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